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# Intelligent Classification and Prognostics of Discharge Pulses and Wire Breakage in WEDM of Ni-Based Superalloys using Advanced Machine Learning Techniques

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## Abstract

*Wire Electrical Discharge Machining (WEDM) offers substantial benefits when cutting difficult-to-cut materials, such as Ni-based superalloys. However, common concerns, including wire breakage and unpredictable discharge pulses, offer significant difficulties to productivity, surface integrity, and process sustainability. This paper proposes an advanced Machine Learning (ML) framework for intelligent discharge pulse categorisation and wire breakage prediction. Raw voltage and current data were captured during WEDM to extract essential pulse properties, which were then utilised to train classification models such as Artificial Neural Networks (ANN). The ANN model obtained a 98% pulse classification accuracy, efficiently discriminating normal, short circuit, and arc discharges in wire breakage prediction based on input data such as peak current, spark gap voltage, and pulse lengths.*

**Major Findings:** *The study found that high arc and brief discharges increase surface roughness and the chance of wire rupture. This ML-driven strategy provides a strong platform for real-time monitoring, fault prediction, and process optimisation in WEDM of superalloys.*

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**Keywords:** *ANN, ML, Roughness, WEDM*

## 1.0 Introduction

Wire Electrical Discharge Machining (WEDM) is a non-traditional machining technique that has transformed how difficult-to-machine materials are shaped and completed. Unlike traditional machining methods that rely on mechanical cutting forces, WEDM works on the thermoelectric erosion principle, employing a constantly moving wire electrode to create regulated spark discharges between the tool and the workpiece in a dielectric medium[1,2]. WEDM is unique in its ability to machine complicated shapes in conductive materials regardless of their hardness or toughness because of its non-contact material removal method. Among the various applications of WEDM, the machining of Ni-based superalloys has gained significant attention due to the rising demand for these materials in high-performance industries such as aircraft, gas turbines, and nuclear energy systems[3-5].

Ni-based superalloys, such as Nimonic 263, have outstanding high-temperature strength, corrosion resistance, and creep resistance, making them ideal for use in demanding service conditions. However, these same qualities make them incredibly difficult to manufacture with traditional methods[6]. WEDM is a feasible option for producing complicated components from these alloys with great accuracy. Nonetheless, the use of WEDM in industrial settings is limited by process inefficiencies and repeated machining failures, particularly wire breakage and unpredictable discharge conditions[7,8]. These challenges not only disrupt the production workflow but also lead to higher energy consumption, reduced productivity, and impaired surface integrity of the produced components.

One of the most difficult aspects of attaining consistent and dependable performance in WEDM is the stochastic character of the spark discharges, which are extremely susceptible to changes in the Inter-Electrode Gap (IEG), dielectric state, and process parameters. These changes produce a wide variety of discharge types, including normal discharges, short circuits, arc discharges, and open circuits[9,10]. Each discharge type has a unique effect on the machining output. For example, typical discharges are preferable for material removal, but high arc or short discharges might degrade surface quality and increase the risk of wire breakage[11]. As a result, a precise and real-time categorisation of discharge pulses is crucial for understanding process dynamics and proactively recognising undesirable machining conditions.

Traditionally, discharge pulse categorisation depended on threshold- or rule-based techniques that analysed current and voltage signals[12]. Early research sought to establish set threshold levels for classifying various types of discharges. Liao and Woo, for example, employed waveform properties to discriminate between normal and pathological pulses, but later researchers created rule-based models based on experimentally determined thresholds[13-15]. While these methodologies gave first insights into discharge behaviour, they had inherent limitations. Most importantly, they require specialist knowledge to establish rules, lack generalisability across multiple machines and parameter settings, and cannot react to new data or changing process circumstances.

Furthermore, these threshold-based models lack the potential to learn or self-improve, rendering them unsuitable for incorporation into intelligent monitoring systems[16]. This has resulted in a pressing demand for data-driven, adaptive systems capable of autonomously classifying discharge pulses with high precision and consistency. Recent breakthroughs in Machine Learning (ML) provide intriguing approaches to resolving these difficulties. When properly trained, ML systems can learn complicated, nonlinear connections from big datasets and generalise effectively across several contexts[17,18]. Compared to static rule-based models, ML-based classifiers may be retrained with fresh data to constantly improve their prediction performance.

In this regard, the current study provides a machine learning-based framework for intelligent discharge pulse categorisation and predictive analysis of wire breakage during Ni-based superalloy WEDM. The originality of this study resides in its simultaneous focus on pulse categorisation and failure prediction, which provides a full perspective of WEDM process health[19,20]. During machining, raw voltage and current signals are recorded and processed to derive key time- and frequency-domain parameters that describe the underlying pulse characteristics. These characteristics are used to train and assess machine learning models such as ANN, Decision Trees, Random Forests, Gaussian Naïve Bayes, and Logistic Regression.

Among these models, ANN has exhibited higher accuracy in categorising discharge pulses into normal, arc, short, and open discharges, with classification accuracies of up to 98%. The ability to accurately identify damaging pulse types allows for a better understanding of the elements that contribute to process instability[21]. The prediction of wire breakage is also addressed using binary classification models based on machining parameter combinations such as Peak Current (IP), Spark Gap Voltage (SV), pulse-on time (Tonne), and pulse-off time (Toff). Random Forest models have achieved perfect classification accuracy (100%) on test data, demonstrating their resilience in detecting parameter regimes likely to cause wire rupture.

The combination of these categorisation and prognosis models creates an effective tool for real-time process monitoring and control[22,23]. By correlating discharge parameters to machining outcomes such as surface roughness, material removal rate, and failure likelihood, the system allows for more informed decision-making in order to maximise process efficiency and product quality[24,25]. For example, the study found that a high proportion of arc and short discharges in the pulse cycle (more than 80%) considerably increases the risk of wire breakage and surface deterioration. Thus, prompt identification and mitigation of these unfavourable discharges can avert catastrophic failures and lower the rework or scrap rate.

Furthermore, the proposed ML models' generalisability allows them to be tailored to varied machine settings and workpiece materials, as long as adequate training data is available[26,27]. This addresses a major shortcoming of rule-based systems, which frequently require machine-specific calibration and are not easily transferred[28]. The automatic learning capacity decreases reliance on operator skill and opens the way to completely autonomous production systems in the future.

This work adds to the continuous growth of intelligent manufacturing systems by introducing a data-driven method to discharge pulse categorisation and wire breakage prediction in WEDM[29-30]. The study uses sophisticated machine learning approaches to solve long-standing issues in the machining of Ni-based superalloys, such as process variability, monitoring complexity, and failure unpredictability[31]. The results of this research open the way for the adoption of smart diagnostics and adaptive control systems in WEDM, increasing its attractiveness as a dependable and high-precision manufacturing solution for next-generation engineering materials.

## 2.0 Material

In the current study, Inconel 718 was chosen as the workpiece material because it is widely used in high-performance engineering domains such as aerospace, oil and gas, and cryogenics, where superior thermal and mechanical qualities are required. A zinc-coated brass wire electrode with a diameter of 0.25 mm was used for machining operations due to its greater electrical conductivity, better flushing properties, and improved performance when compared to other standard wire materials. To analyse discharge behaviour, a series of 50 mm long straight cuts were made on a 10 mm thick Inconel 718 specimen using a precision-controlled WEDM system.

The trials were conducted using an EDM machine. To model a wide range of discharge behaviours and probable machining failures, machining parameters such as servo voltage, pulse-on duration, and pulse-off time were systematically changed, as shown in Table 1. The acquired signals were post-processed using MATLAB. A low-pass filter was applied to raw voltage and current data at a passband frequency of $6 \times 10^{-10}$ π radians/sample to reduce noise and increase signal interpretation accuracy.

The technique used in this paper focuses on a careful investigation of electrical discharge pulses, which exhibit considerable differences in their time-domain features under various machining circumstances. These pulses have been shown to contain embedded information on machining stability, material removal efficiency, and probable problems such as wire breakage and spark loss. These failures are often caused by inadequate debris clearance from the inter-electrode gap, which results in

**Table 1.** EDM parameters

| S. No. | Details | |
|---|---|---|
| 1 | WED wire Diameter | 0.3 |
| 2 | Current | 15,50 |
| 3 | Feed | 5, 10 |
| 4 | Voltage | 30, 45, 60 |
| 5 | Time ON | 100, 120, 130 |
| 6 | Time OFF | 40, 60, 70 |

unstable sparking conditions and excessive wire heating. Classifying discharge pulses into relevant categories allows one to indirectly monitor debris collection and infer the general health of the machining zone.

To do this, numerous important characteristics were retrieved from the pre-processed voltage and current waveforms. These include discharge duration (the entire amount of time that current flows between electrodes), ignition delay time (the amount of time it takes for the dielectric medium in the gap to break down and trigger a discharge), discharge voltage (the voltage between the electrodes during discharge), and input current. These parameters were chosen for their significance to spark initiation and propagation dynamics, as well as their known relationship with machining efficiency and failure onset.

The experimental procedure began with the measurement of voltage and current signals under both stable and unstable milling conditions. Limiting machining conditions representative of failure-prone scenarios were intentionally produced utilising increased discharge energy and restrictive flushing configurations, such as smaller spark gaps and shorter pulse-off periods. These datasets contained a wide range of pulse behaviours required for effective machine learning model training. Based on distinctive pulse properties, each collected signal was manually classified into one of four discharge classes (normal, arc, short circuit, or open circuit), laying the groundwork for the supervised learning technique. The final dataset consisted of 1000 labelled examples, with 250 samples representing each discharge type.

To automatically categorise discharge pulses, a machine learning-based classification technique was used. The model used was an ANN with a 1000 × 5 input matrix including four pulse characteristics and a class label for each instance. During the training phase, a 5-fold cross-validation approach was used to confirm that the ANN model generalised well to previously unknown data and did not overfit. The ANN design, including the number of hidden layers and neurons per layer, was optimised iteratively based on classification performance criteria such as accuracy and the F1-score. The performance of the ANN model was compared to other machine learning classifiers, such as Decision Trees, Random Forests, Logistic Regression, and Gaussian Naïve Bayes, to find the best technique for the application. A supplementary validation dataset with 100 fresh data points was utilised to test the final model's resilience and predictive capacity.

In the study's last phase, a thorough examination was undertaken to determine the link between different pulse kinds and machining outcomes, notably in terms of surface quality, material removal efficiency, and wire breakage events. It was discovered that the frequency of arc and short circuit discharges was strongly related to inadequate debris evacuation and wire warming, which considerably increased the probability of wire breakage. These findings highlight the vital necessity of real-time pulse categorisation in predictive diagnostics and adaptive control systems in WEDM.

## 3.0 Experimental Method

The overall pulse classification approach and experimental setup are given in Figure 1.

Predicting occurrences based on current data may be especially difficult in complex industrial processes like wire EDM. In such instances, supervised learning models, such as classifiers, are typically recommended, as shown in Figure 2.

Classification is a popular machine learning approach for determining the category or class to which a specific data item belongs. From a geometric approach, classification entails determining a decision boundary that effectively divides several groups of data points in a particular feature space. Depending on the data's complexity and dimensions, this boundary can be a line, a surface, or even a high-dimensional hypersurface. As the number of characteristics rises and their relationships get more sophisticated, the classification process becomes more complex, frequently needing large computational resources.

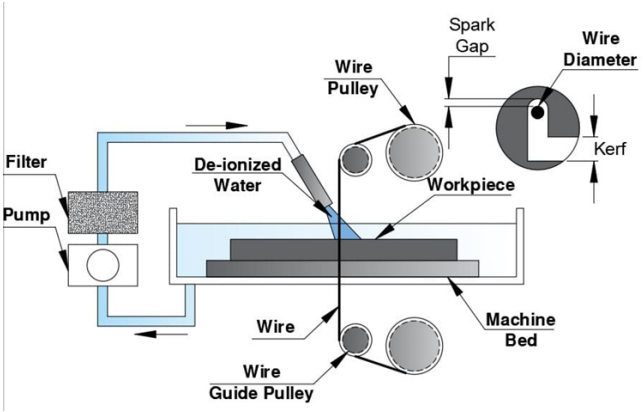



**Figure 1.** Set up a block diagram.

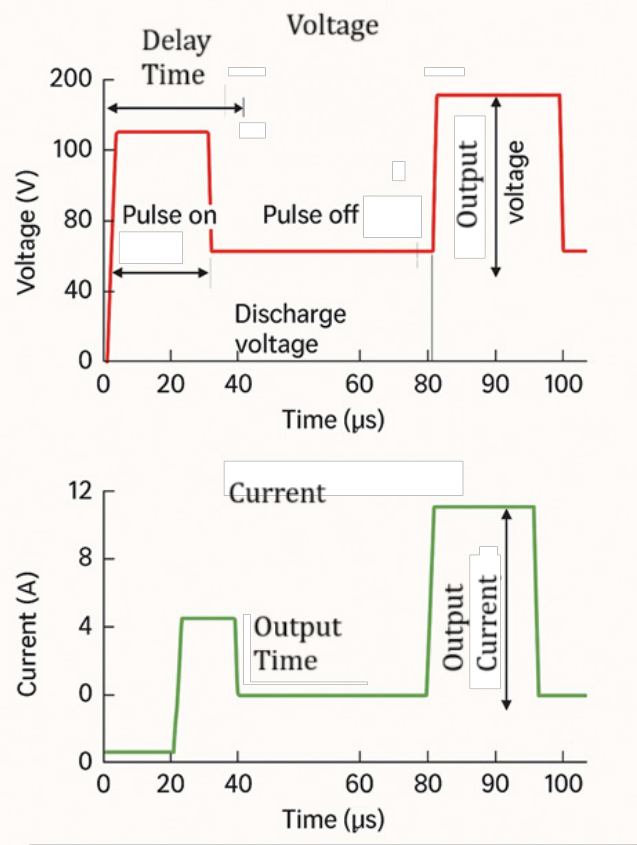



**Figure 2.** Output cycle of EDM.

Among the different classification techniques available, ANNs have acquired popularity due to their high prediction accuracy, flexibility, and robustness when dealing with noisy and non-linear data. ANNs are made up of layers of linked nodes, or "neurones," with each connection having its trainable weight and bias. During the training phase, these parameters are iteratively changed to reduce prediction error and improve the model's learning ability. An ANN's design may be adjusted by adjusting the number of layers and neurons per layer, giving significant flexibility in modelling very complicated datasets, like as those created in wire EDM operations.

In the context of WEDM, particularly during the machining of Ni-based superalloys such as Inconel 718, discharge pulses display nonlinear patterns that are impacted by various interacting process factors. ANNs are highly adapted to learning such patterns and identifying various pulse kinds, which are crucial for anticipating machining stability and avoiding problems like wire breakage. Previous research provides a full description of the application of ANN models for categorising WEDM responses and their usefulness in real-time monitoring[16].

## 4.0 Results and Discussion

Figure 3 depicts several discharge pulse forms derived from collected signal data. These pulse forms differ significantly from the idealised waveforms usually used in prior investigations. Even within the same pulse type (such as short circuits), there are considerable variances in waveform shape, amplitude, frequency, and duration. Similar discrepancies are visible in arc and normal discharge signals as well. This vast variety in pulse characteristics underlines the difficulty of using fixed threshold-based classification algorithms, which are frequently insufficient due to the overlapping nature of feature values between categories. This emphasises the need for more advanced and adaptable categorisation approaches, such as machine learning.

To address this complexity, five machine learning classifiers were tested on the same dataset with a 5-fold cross-validation technique in Figure 4. The classifiers used were Decision Tree, Naïve Bayes, Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and ANN. The ANN model achieved the best prediction accuracy, as shown in Table 2. The best-performing ANN design was made up of three hidden layers, each with 20 neurons (4-20-20-20-4 arrangement). This structure was finalised after testing many configurations with hidden layers ranging from one to ten, while keeping a consistent neuron count per layer. The training approach included iterative optimisation of weights and biases to minimise classification error. The trained model returns the chance that a particular pulse belongs to one of four preset categories: Normal Spark, Arc Spark, Short Spark, or Open Spark. The class with the highest probability is chosen as the projected outcome.

In Figure 5, the model has a remarkable validation accuracy of 98.3%, correctly predicting 983 out of 1,000 samples. The confusion matrix in Figure 6 depicts the model's prediction performance for each class. For example, in 98.4% of instances, the ANN correctly detected typical sparks (Class 1), with slight misclassifications (0.4% as arc sparks and 1.2% as open sparks). Similarly, the categorisation accuracy for arc, short, and open sparks was 98.4%, 98.4%, and 98%, respectively.

Figure 6 depicts a Receiver Operating Characteristic (ROC) curve that was used to further analyse the

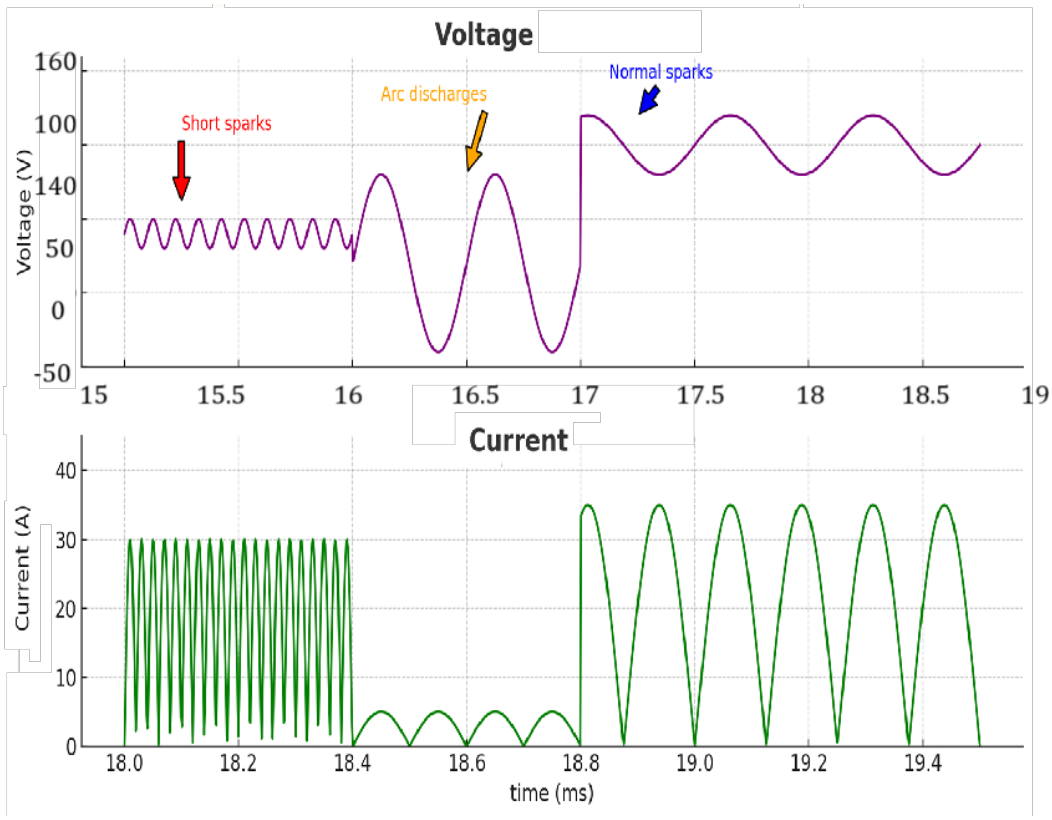



**Figure 3.** EDM discharge cycle.

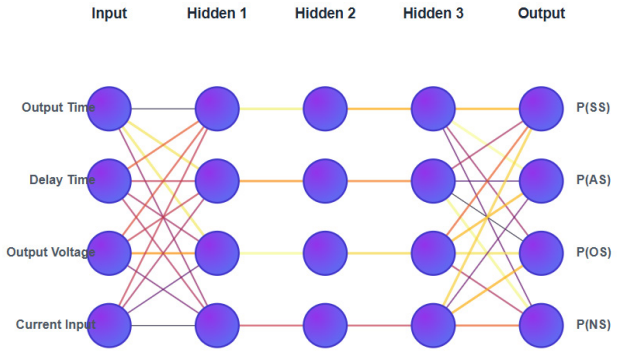



**Figure 4.** ANN structure model.

**Table 2.** Various ML model comparisons

| S. No. | Different ML models | Accuracy (%) |
|---|---|---|
| 1 | ANN | 99 |
| 2 | KNN | 93 |
| 3 | SVM | 91 |
| 4 | NB | 90.2 |
| 5 | Decision Tree | 88 |

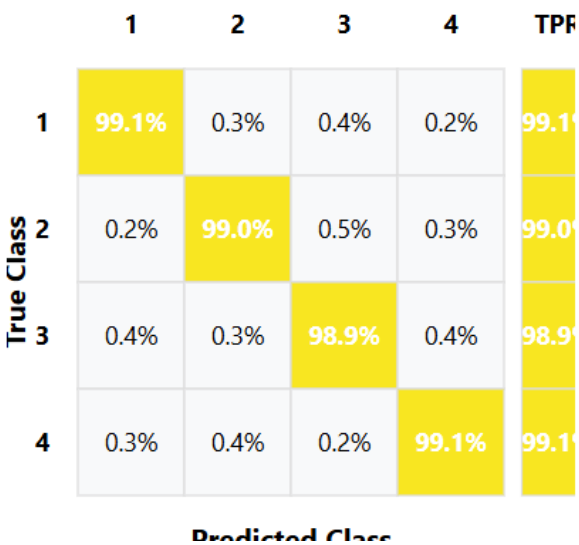



**Figure 5.** ANN matrix.

performance. For Class 1 (normal spark), the ROC curve virtually crosses through the optimum point (0,1), implying a 98% true positive rate with few false positives. Comparable ROC profiles were observed for the remaining classes, demonstrating the resilience and

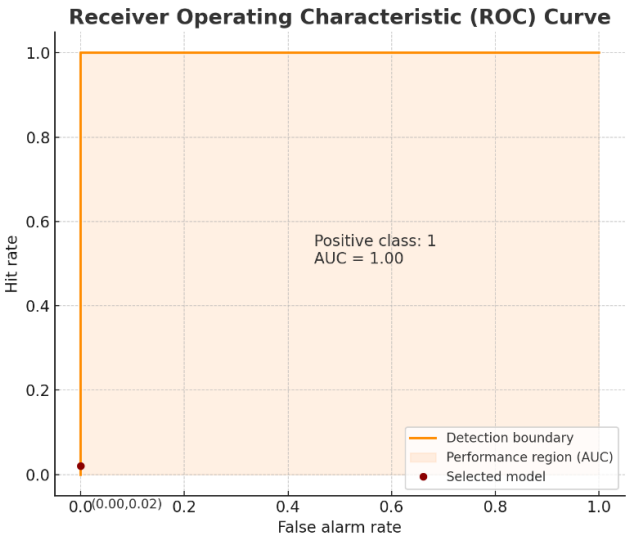



**Figure 6.** ROC curve.

accuracy of the ANN model in categorising complex and noisy pulse signals common to the WEDM process.

## 4.1 ANN Performance Verification

A confusion matrix is used to validate the performance of the trained ANN classifier in the actual world. Figure 7 depicts the results of assessing the model's performance using 100 previously unreported data points. The model has an overall prediction accuracy of 98%. Class-wise prediction accuracy is 96%, 96%, 100%, and 100% for classes 1-4.

## 4.2 Effects of Discharge Pulses on Machining Performance

This section discusses how different discharge pulse types affect surface quality, machining efficiency, and failure

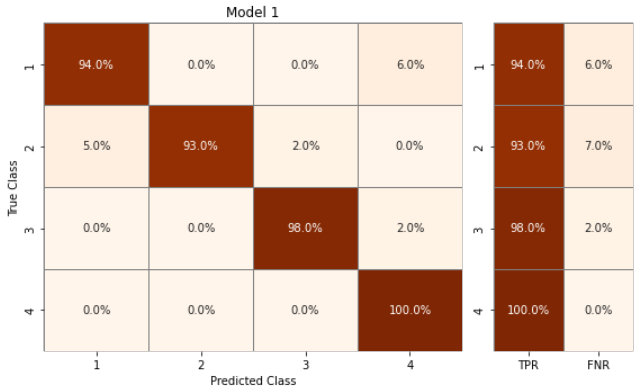



**Figure 7.** Trails carried on ANN matrix.

occurrences during Inconel 718 wire EDM. To assess the impact, the relative fraction of each discharge type was computed using a pulse counter, which measures the ratio of individual pulse occurrences to the overall number of pulses recorded.

Short circuits and arc discharges were discovered to have an unfavourable effect on the surface finish. These pulses often occur at higher frequencies and contain more discharge energy, resulting in deeper craters and a rougher surface roughness. Figures 8(a, b) show a comparison of machined surfaces with varying proportions of arc and short discharges-0.6 in the first example and 0.2 in the second. In the scenario with a larger fraction (0.6), the surface has visible flaws such as tiny globules and thick recast layers, suggesting poor surface integrity. In contrast, when arc and short discharges are less common, the surface seems more uniform and smoother, attributable to the creation of well-distributed and overlapping micro craters under steady discharge circumstances.

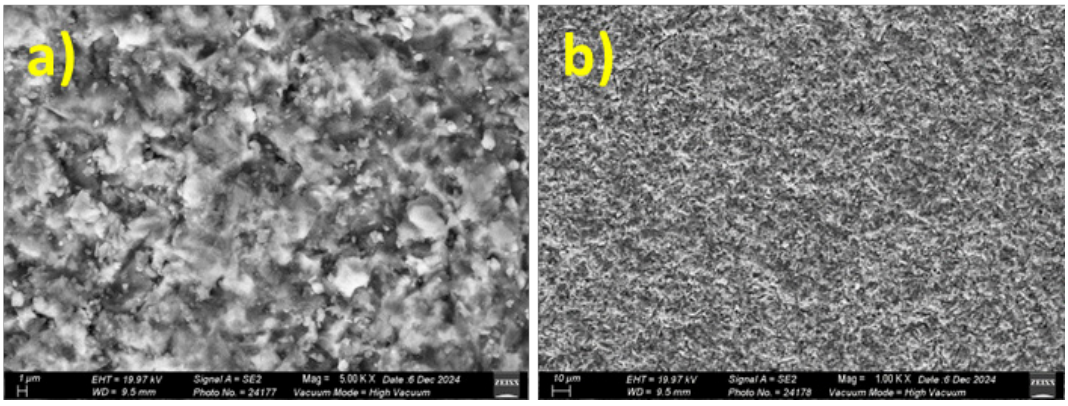



**Figure 8.** Short spark SEM image.

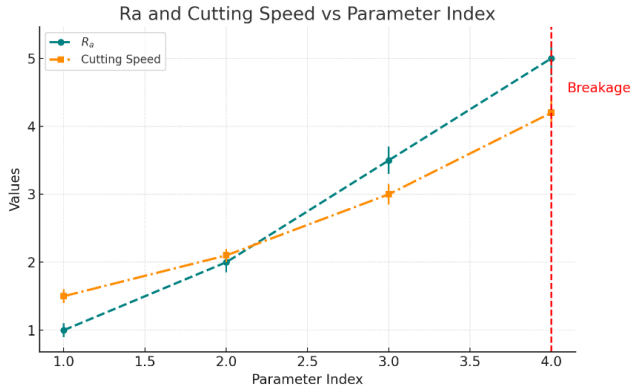



**Figure 9.** Surface roughness and cutting speed.

When the combined proportion of Arc Sparks (AS) and Short Sparks (SS) is large, the material removal rate increases, but at the expense of reduced component quality. Figure 9 depicts a clear trade-off between cutting speed and surface Roughness (Ra). In addition to decreasing the surface polish, a high number of arcs and short discharges during a pulse cycle indicate process instability, which can considerably increase the risk of wire breakage. As indicated in Figure 9, when the total percentage of AS and SS surpasses 80%, incidents of wire breaking become apparent.

Although various studies have developed models for forecasting machining failures based on discharge patterns, their usefulness has frequently been hampered by mistakes in identifying pulse types. Figure 10 shows how different discharge pulse compositions connect with particular failure types. During wire-breaking events, short sparks were the predominant pulse type, but during times of spark absence, open sparks were more abundant in the cycle.

## 5.0 Conclusion

This work describes a machine learning-based method for identifying discharge pulses in wire EDM and investigates their impact on machining performance and failure mechanisms while treating Inconel 718. The study of pulse signals revealed four unique discharge types: normal, arc, short, and open. Multiple classification models were tested, and the ANN model had the greatest classification accuracy (98.3% during training and 98% during verification). The ANN model's strong performance demonstrates its capability for collecting complicated patterns in pulse data. The data demonstrated

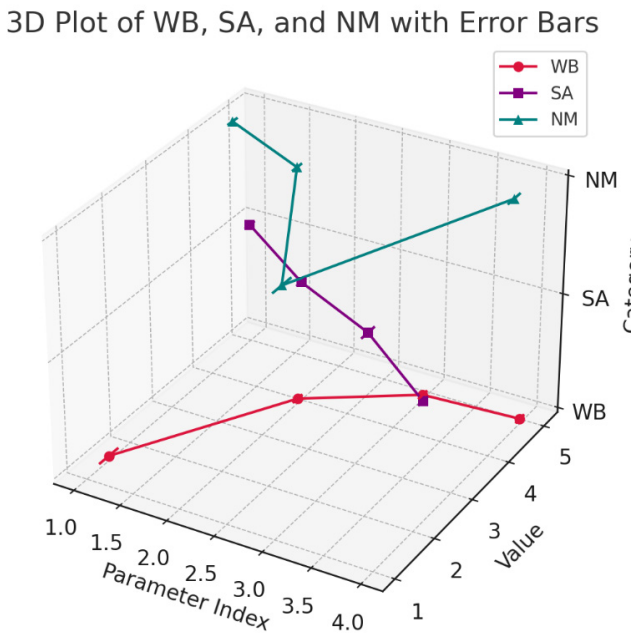



**Figure 10.** Output of machining.

that a large proportion of arc and short pulses had a considerable impact on surface integrity, resulting in rougher surfaces with an observed increase of up to 74.1% in Ra. Furthermore, when the total number of arcs and short sparks approached 80%, machining instability increased, frequently resulting in wire breakages. These findings highlight the significance of intelligent pulse categorisation for real-time monitoring and failure prevention in WEDM of Ni-based superalloys.

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